CHAPTER -7

FINDINGS, SUGGESTIONS AND CONCLUSION

7.1. FINDINGS

The amount of risk assessed and that now experienced in respect of these clients were found to be the similar in case of weighed average model. Clients with high scores and low risk have been prompt payers on the other hand; those with low scores and high risk were found to be defaulters.

The following are the key findings of each of the model

Weighted Average Model - Findings

- From the survey it was found that 95 percent of the bankers responded that quantitative parameters interest them more than qualitative parameters.

- Quality of Information – 85 percent of the bankers felt that quality of information and timely information is a key to the assessment and is important in expediting decisions regarding credit sanctioning.

- Quality of Information - 88 percent of the bankers expressed that time lag between the supply of quality information and delays in credit decision are root cause of the credit risk problems.

- From the survey it was also observed that majority of the bankers depend on third party assessment for second line of defence.

- Even SME sector constitutes 80 percent of industries in India, 78% of bankers would like to avoid taking risk by giving credit to SMEs.

- It was observed that many existing models of bank have 90 percent of subjectivity and assessment is not aided by tool.

- Further it was found that because of this subjectivity, add influence of government and RBI norms, bankers are constrained to make decisions.
• From the field observations it was found that the definite and distinct pattern of credit authorization. For example from 2004 -05 to 2006 – 07. Bankers’ preference was IT & ITES industry category. In the period 2005-06 to 2008-09 Real Estate received favourable decisions.

**Design Development of Model - Findings**

• The existing models available in the market does not have all these features which are required for ease of use of bankers

Features are

1. Rating Scale

2. Grading or Classification of Assets

3. Discriminant Functionality

• Models available are either too subjectivity based models prone to judgment of individual bankers or too much application of Mathematical and Statistical Model (based on probability).

• Mathematical and Statistical models are very difficult for bankers to apply to real time issues even though 95 percent of them prefer quantitative data of clients.

• All these issues were considered while developing proposed model. The above mentioned three features are addressed in the model for ease of use.

• Majority of the models existing in the market are not the helping tool or aid for assessment. In this model aiding tool has been provided in the form matrix which guides the Credit Manger in scoring and also in classification of the assets.

• Majority of the models built on fewer variables or on Altaman’s Z – Score. In this model 31 both quantitative and qualitative variables are considered for study which is an exhaustive and comprehensive variable to determine credit worthiness of the client.
• About 81% of the original cases were classified correctly according to the existing model. i.e. the predictive power of the existing/current model is 81 percentage.

• About 94.28% of the original cases were classified correctly according to the weighted average model, i.e. the predictive power of the weighted average model is 94.28%

• Financial risk is considered to be the most significant of all the risks.

• While management risk falls next in the line, the business risk is rated third in its vitality.

**Discriminant Model Findings**

• On an average of 81% of the original cases were classified correctly according to the existing model. i.e. the predictive power of the existing/current model is 81 percentage

• About 85.71% of the original cases were classified correctly according to the discriminant model. (i.e. the predictive power of the discriminant model is 85.71%)

• Weighted average model along with Discriminant Model can be used for predicting the credit worthiness of the clients because it has higher predictive power.
SUGGESTIONS

Primary Objectives

1. To design and develop a credit rating model for evaluating risk based on Phases of Economic Cycle

   Refer to the Annexure – II for Credit Rating Model Based on Economic Cycles completely tested and validated with results see chapter -3.

2. To develop Economic Indices Scale based on industrial growth and contribution to the GDP for industry risk assessment and evaluation.

   To address this issue Market Risk classification has introduced several parameters based on Industrial and Business Cycle of the business. (Refer to Market Classification of proposed model)

3. To develop Economic Transformation Change Process and Control Technique Matrix for ease of implementation of the defined model.

   Refer to Table 3.14 Key for Assessment which was an useful tool for Credit Managers in assessing quality of the assets with subjectivity or biased judgment. Rating scales created for each parameter is on the basis of industrial standards and industrial credit rating practices. This key for assessment tool is very important in monitoring progress of the high risk class clients and helps in advising client regarding the steps the client has to take in future.
CONCLUSION

Proposed Credit rating and scoring model present a distinct set of challenges to model validation. The primary event of interest default is rare. When defaults do occur, they tend to happen in batches, implying long spells during which defaults are rarer and depend on business cycle of the industries. All of this means that the comparison of model predictions to outcomes back testing is statistically powerful. Adding to the level of difficulty of the validation challenge, there is a shortage of generally accepted standard models against which it is to be compared. Recognizing the challenges of model validation for credit rating and scoring models becomes increasingly important that the users of those models employ a complete process thatoffsets the limitations of any individual test.

The first element of that process is to demonstrate that the model is well developed. For proposed Model at least 20 existing models were studied and made model logical on an a priori basis. Models need to be supported with empirical evidence that they can identify credit risks in a data set that is well designed for model development purposes. This has been done adequately done to see whether this model stands and proved that it is apt in its application. Modelers should be sensitive to the risk of trying to describe a development data set perfectly when some of the outcomes in the developmental data may be random. This issue was well addressed in this model. Given a well-developed model, the second element of the process is ongoing verification that the model is working as expected. Ongoing verification includes activities designed to confirm that the model is implemented as designed and activities designed to get an early read on whether the models is likely to be working. Process verification includes checking equations and the computer code that deploys the model. Equally important, process verification must include mechanisms to assure the quality of the data inputs. Process verification includes the evaluation of reports to confirm that they are understandable and well used. The proposed model is given to five nationalized banks for their use and results obtained are proving that model indeed is working. Another key aspect of ongoing verification is the comparison of model predictions to predictions from other useful sources benchmarking to confirm the likely correctness of the predictions. The five banks are using this model along
side their own model and comparing results. So far results are very encouraging proposed model is performing with more accuracy which was demonstrated through discriminant analysis. The third element of model validation is outcomes analysis. In this phase, where practicable, model predictions are compared to actual outcomes. While theoretically compelling, model users must understand that statistically powerful outcomes tests may be rare, and must not count on this evidence alone. All five banks are continuously using this model and researcher is monitoring the performance along side actual performance of the companies.

**Proposed Credit Rating Model-Risk Analysis in the Basel II Context**

The advent of regulatory capital requirements that will be a function of internal bank credit risk assessments raises the stakes for model validation. While Basel II is a regulatory capital framework, bank management will be responsible for model validation; bank validation processes will be the first line of defence against bad credit risk models. Just as Analysts do in other risk management contexts, bank Credit Managers will examine the bank validation processes. It must be recognized, however, that the added importance of being part of the capital framework means that some validation deficiencies that Credit Managers might otherwise have deemed immaterial will be brought to management’s attention. So this model works along side the existing model to form first line defence in identifying potential Non performing assets.
SCOPE FOR FURTHER RESEARCH

Increasing international competition and changes in the regulatory framework driven by the Basel Committee on Banking Supervision (Basel II) called forth incentives for banks to improve their credit rating systems. In a competitive framework a poor statistical power of a bank’s internal rating system will deteriorate the economic performance due to adverse selection, i.e. customers with a better credit quality than assessed by the bank will potentially walk away and leave the bank with a portfolio of customers with a credit quality lower than estimated. Obviously, improving the statistical power of a rating system will have a positive impact on economic performance. Financial firms and their regulators are comfortable thinking about financial risk, credit risk, market risk, and interest rate risk. While it would be convenient if Analysts could physically observe and measure those risks, but Analysts cannot. Therefore, among the tools that Analysts use to think about those risks are models to identify and quantify them. Here is an effort made in this research work in Design and developing credit rating model based on economic indicators. The fact of designing this model is in such a way that it is intrinsic to the notion of models that their feature risk has been demonstrated. In the realm of finance modelling, the object of interest is future outcomes, either expected or potential and those modelled outcomes can be wrong. Humans construct models, so models are exposed to all of the sources of error of any other human construct errors in logic, errors in execution, and errors in use. Those errors are what Analysts call model risk. However, determining whether models are wrong is difficult. While building this proposed model much care has been taken to minimize the human subjectivity and hence the model has fewer model deficiencies (model risk). This point also proved by Wilks’ Lambda test and thorough model validation by using the data of clients from different banks over a period of five years. It is often said, but still true; that all models are wrong by design, because they are simplifications of reality. Proposed Model reflects knowledge, beliefs or assumptions about important casual relationships. Those causal relationship statements of this model are, by design, highly abstract. They are not designed to capture every detail of reality, including the idiosyncratic factors that contribute to observed outcomes. Furthermore, when models are used to generate predictions and risk models are included in that classes the ‘predicted’ outcomes
reflect future outcomes of exogenous variables. Even a very good statement of the causal relationship will deliver wrong predictions under most outcomes for the exogenous variables. So the modelled outcomes are conditional on a very precise artificial construct and specific set of conditions. Under the most favourable circumstances, tests of such models are probability statements; this model is designed in such a way that under most circumstances model adequacy is determined by expert judgment. While this is a disturbing notion for the non-modeller, it is the one that must be confronted because it determines strategic choices in model building, model administration and model use.

**Model-Risk Analysis**

The appropriate response to model risk is to manage the risk in the use of models, just as Analysts manage the risks of all other aspects in running the enterprise. Proposed model has provided adequate matrix tool which help the Credit Manager in scoring, rating and classifying the clients. The objective of this model builder is to devise the best model for the business use; the objective of model-risk management is to determine whether that has been accomplished. Model users must acknowledge at the outset that models are imperfect and put in place a process for controlling the risk that they are not good enough to use. Model users need to employ a model validation process that is designed to provide the best available evidence that a model is good. Such a process entails the evaluation of model development, verification that it is operating as planned, and monitoring for evidence that contradicts the model. The model validation process is subjected to individual bank necessity to apply the model with more accuracy and circumspective. Hence there is a scope for developing new models with higher accurate prediction power.